DOI: 10.3901/CJME.2010.**.***, available online at www.cjmenet.com; www.cjmenet.com.cn

Multi-objective Optimization Conceptual Design of Product Structure Based on Variable Length Gene Expression

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Received October 13, 2009; revised July 26, 2010; accepted August , 2010; published electronically August , 2010

Abstract: It is a complicated problem for the bottom-to-top adaptive conceptual design of complicated products between structure and function. Reliable theories demand to be found in order to determine whether the structure accords with the requirement of design. For the requirement generally is dynamic variety as time passes, new requirements will come, and some initial requirements can no longer be used. The number of product requirements, the gene length expressing requirements, the structure of the product, and the correlation matrix are varied with individuation of customer requirements of the product. By researching on the calculation mechanisms of dynamic variety, the approaches of gene expression and variable length gene expression are proposed. According to the diversity of structure selection in conceptual design and mutual relations between structure and function as well as structure and structure, the correlation matrixes between structure and function as well as structure and structure are defined. By the approach of making the sum of the elements of correlation matrix maximum, the mathematical models of multi-object optimization for structure design are provided based on variable requirements. An improved genetic algorithm called segment genetic algorithm is proposed based on optimization preservation simple genetic algorithm. The models of multi-object optimization are calculated by the segment genetic algorithm and hybrid genetic algorithm. An example for the conceptual design of a washing machine is given to show that the proposed method is able to realize the optimization structure design fitting for variable requirements. In addition, the proposed approach can provide good Pareto optimization solutions, and the individuation customer requirements for structures of products are able to be resolved effectively.

Key words: gene expression, multi-object optimization, conceptual design, genetic algorithm

1 Introduction

For research on the conceptual design of products, TAN, et al[1], gave a bottom-to-top adaptive design respect and a design model of bottom-to-top six-step adaptive process. Bottom function of adaptive design usually has many corresponding structures and each structure sometimes matches with many functions. For the complex product design process, it is necessary that a reliable theory is found to decide if the design structure is suit for requirement. Structure option is a typical optimization problem of mathematic combination, proper mathematic optimization algorithms need to be found out. GÁBOR, et al[2], gave a summary to this problem; LI, et al[3], gave an optimization frame structure of bottom-to-top adaptive design for research on total description and uniform expression for evolutional design modes. As an intelligent tool, genetic algorithm takes strong advantage in solving optimization problem. HSIAO, et al[4], studied the shape optimization conceptual design and gave a new product shape by means of genetic algorithm combined with neural networks. TORSTENFELT, et al[5], extended single product to the optimization process of product chains and proposed a mathematic approach of product chains optimization by topology methods. In use of correlation matrix approach, ZHAO, et al[6–10], extended single-object to multi-object optimization modes and established a multi-object calculation model from function requirements to structures by the correlation matrixes, then proposed a uniform optimal calculation model for conceptual design and solved it out by genetic algorithm. CHEN, et al[11], researched on bottom-to-top conceptual design problem by means of fuzzy immune algorithm and gave a fuzzy multi-object optimal mathematic model. In use of shipping design as an example, OLCER[12] proposed a hybrid optimal approach to solve the optimization problem for ship design and

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This project is supported by National Natural Science Foundation of China (Grant No. 50975033, Grant No. 60875046), and Program of Education Office of Liaoning Province, China (Grant No. LT2010074)

confirmed the result by multi-object genetic algorithm. At present, the structure optimization design based on genetic algorithm needs further research.

The above design process supposes function requirements of the product as static, but as time goes on, new requirements are to be added in the set, old requirements are removed from the set and new requirements bring about new structures. In the mean time, the length of gene chains for expressing product functions is changed which means that the content of initial product information cannot be used in the database, so the product must be renewed design. A lot of time and human resources are wasted.

This paper proposes an approach of multi-objective optimization conceptual design of product structure using variable length gene expression. In the stage of the bottom-to-top adaptive conceptual design, the variable requirements of product are expressed with variable gene formulation, and then the multi-object optimization model can be established and calculated by segment genetic algorithm. The purpose is that when a new requirement comes, initial design information also can be used. The design task can be completed by corresponding changes to the initial design information. Consequently, the experiment results for washing machine structure design are completed and simulated by segment genetic algorithm and hybrid genetic algorithm.

2 Variable Length Gene Expression

2.1 Gene expression of product

It is very important for conceptual design of complicated products by the quantitative expression of design process, which can make automatic achievement of conceptual design easy. So each element of products, such as function, behavior, structure, and carrier, can be named as design elements in the design process. Gene expression of design elements can be defined as follows.

Definition 1: Gene expression of design element. Give a design element, such as function, behavior or structure, as an ordered set $\boldsymbol{F}_k$, $k=1, 2, \cdots, n$, and let it be a n-dimensional vector. According to its position, establish a n-dimensional vector $\boldsymbol{f}$, $\boldsymbol{f}=(f_1, f_2, \cdots, f_n)$, whose value equals to 0 or 1, that is:

$$f_k = \begin{cases} 1, & \text{included in } \boldsymbol{F}_k, \\ 0, & \text{excluded in } \boldsymbol{F}_k, \end{cases} \quad k = 1, 2, \cdots, n. \tag{1}$$

Then the vector $\boldsymbol{f}$ is named as gene expression of design element for the given product, which includes requirements gene expression, function gene expression, structure gene expression, behavior gene expression, and carrier gene expression, etc.

2.2 Variable length gene expression

The changes of ordered set $\boldsymbol{F_k}$, $k=1, 2, \cdots, n$, can result in the changes of the gene expression of each vector. However, the changed gene expression can be figured out by the previous gene expression. So if we want to add or delete some element from a certain position, shown as Fig. 1 and Fig. 2, original gene position should be moved horizontally.

(1) Add the design elements of s number after the position i. Suppose the initial gene expression vector of a design element is $(b_1, b_2, \cdots, b_i, \cdots, b_n)$, and the finial gene expression vector is $(c_1, c_2, \cdots, c_i, \cdots, c_{i+s}, \cdots, c_{n+s})$, which is shown in Fig. 1, so that:

$$c_j = \begin{cases} b_j, & \text{when } j \le i, \\ \text{adding elements}, & \text{when } i < j \le i+s, \\ b_{j-s}, & \text{when } j > i+s. \end{cases} \tag{2}$$

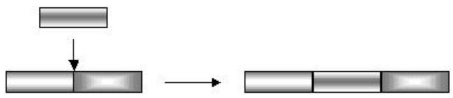

Fig. 1. Change of position when gene segment is added

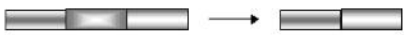

Fig. 2. Change of position when gene segment is deleted

(2) Delete the design elements of s ($s<n$) number after the position i. Suppose the initial gene expression vector of a design element is $(b_1, b_2, \cdots, b_i, \cdots, b_n)$, and the finial gene expression vector is $(b_1, b_2, \cdots, b_i, \cdots, b_{n-s})$, which is shown in Fig. 2, so that:

$$d_j = \begin{cases} b_j, & \text{when } j \le i, \\ b_{j+s}, & \text{when } j > i. \end{cases} \tag{3}$$

3 Correlation Matrix of Products

The first step for achieving an optimization model of conceptual design is to set up a correlation matrix of the products. Due to different methods in the design process, sometimes we need to consider their relationships among design information of function, behavior, structure, and carrier, etc. Now we give definition for correlation matrix of products as follows.

Definition 2: Correlation matrix of products. We can set up 0–5 different levels according to different correlation levels. 1–5 can represent different satisfied value, and the order from 1 to 5 stands for the increasing levels of satisfaction. 0 means irrelative. Suppose a_i ($i=1, 2, \cdots, n$) and b_j ($j=1, 2, \cdots, m$) are design elements, the correlation matrix of products can be shown as follows:

$$\begin{array}{c c} & \begin{array}{cccc} b_1 & b_2 & \cdots & b_m \end{array} \\ \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_n \end{array} & \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{pmatrix} \end{array}. \tag{4}$$

When a_i is correlated with b_j, $c_{ij}=\eta_k$, η_k means one value from 1 to 5. Otherwise, $c_{ij}=0$. When a_i and b_j are the same elements which means $m=n$, $a_i=b_i$, this matrix is named as self-correlation matrix. For example, if a_i means different structures of products and a_i can combine with a_j, then $c_{ij}=\eta_k$. Otherwise, $c_{ij}=0$. As a result, a self-correlation matrix can be achieved. When a_i and b_i are different design elements which means $a_i\neq b_i$, this matrix is named as different-correlation matrix. For example: if a_i means function, b_j means structure, when b_j can achieve a_i, $c_{ij}=\eta_k$. Otherwise, $c_{ij}=0$.

4 Multi-object Optimization Models

Down-to-up design means at the premises of bottom function decomposition, each divided bottom function should be corresponding to conformed multi-structure, and the optimal structure is selected to complete the process of structure combination. Firstly, each bottom function must be matched to one or move structures, and the satisfaction levels of the functions which are achieved by each structure are different. Secondly, there are relationships between one structure and another. Some structures can be combined with others, but some cannot. Furthermore the levels are different. Finally, a multi-object optimization model can be established by correlation matrix.

(1) Function decomposition. Suppose the divided bottom function as a_1, $a_2,\cdots,a_n$. The structures which achieved function a_i mean as b_{i1}, $b_{i2},\cdots,b_{im_i}$, and mark it as the vector $\boldsymbol{B}_i=(b_{i1},b_{i2},\cdots,b_{im_i})$, $i=1, 2,\cdots, n$.

(2) Achieving a correlation matrix between functions and structures. If structure b_{ij} cannot achieve function a_i, the matrix's factor is 0. Otherwise, give it the value from 1 to 5 according to different levels, the matrix is shown as below:

$$
\begin{array}{cc}
 & \text{Structure} \\
 & \begin{array}{cccc} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \cdots & \boldsymbol{B}_n \end{array} \\
\text{Function} \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_n \end{array} & \begin{pmatrix} \boldsymbol{C}_1 & 0 & \cdots & 0 \\ 0 & \boldsymbol{C}_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \boldsymbol{C}_n \end{pmatrix},
\end{array}
\tag{5}
$$

where $\boldsymbol{C}_i$ means the block matrix, $\boldsymbol{C}_i=(c_{i1},c_{i2},\cdots,c_{im_i})$.

(3) Achieving a correlation matrix between structures and structures. If structure b_{ik} and b_{jl} cannot combined together, the factor is 0, otherwise give it the value from 1 to 5 according to different levels. The matrix is shown as below:

$$
\begin{array}{cc}
 & \text{Structure} \\
 & \begin{array}{cccc} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \cdots & \boldsymbol{B}_n \end{array} \\
\text{Structure} \begin{array}{c} \boldsymbol{B}_1 \\ \boldsymbol{B}_2 \\ \vdots \\ \boldsymbol{B}_n \end{array} & \begin{pmatrix} \boldsymbol{D}_{11} & \boldsymbol{D}_{12} & \cdots & \boldsymbol{D}_{1n} \\ \boldsymbol{D}_{21} & \boldsymbol{D}_{22} & \cdots & \boldsymbol{D}_{2n} \\ \vdots & \vdots & & \vdots \\ \boldsymbol{D}_{n1} & \boldsymbol{D}_{n2} & \cdots & \boldsymbol{D}_{nn} \end{pmatrix},
\end{array}
\tag{6}
$$

where $\boldsymbol{D}_{ij}$ means block matrix of row m_i and line m_j, $\boldsymbol{D}_{ij}=(d_{ij}^{k_ik_j})_{m_i\times m_j}$, $k_i=1, 2,\cdots, m_i$, $k_j=1, 2,\cdots, m_j$. $d_{ij}^{k_ik_j}$ is dependent on combined levels of b_{ik_i} and b_{jk_j}. $\boldsymbol{D}_{ij}=\boldsymbol{D}_{ji}$, $\boldsymbol{D}_{ii}=\boldsymbol{I}$.

(4) Achieving a correction matrix between requirements and structures. If the structure b_{ik} cannot satisfy the customer requirement f_{jl}, the element of correlation matrix is 0, otherwise different value from 1 to 5 can be given according to achievement degree. The correlation matrix is shown:

$$
\begin{array}{cc}
 & \text{Structure} \\
 & \begin{array}{cccc} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \cdots & \boldsymbol{B}_n \end{array} \\
\text{Requirement} \begin{array}{c} \boldsymbol{F}_1 \\ \boldsymbol{F}_2 \\ \vdots \\ \boldsymbol{F}_s \end{array} & \begin{pmatrix} \boldsymbol{E}_{11} & \boldsymbol{E}_{12} & \cdots & \boldsymbol{E}_{1n} \\ \boldsymbol{E}_{21} & \boldsymbol{E}_{22} & \cdots & \boldsymbol{E}_{2n} \\ \vdots & \vdots & & \vdots \\ \boldsymbol{E}_{s1} & \boldsymbol{E}_{s2} & \cdots & \boldsymbol{E}_{sn} \end{pmatrix},
\end{array}
\tag{7}
$$

where $\boldsymbol{E}_{ij}$ is the block matrix of row l_i and line m_j, and $\boldsymbol{E}_{ij}=(e_{ij}^{g_ik_j})_{l_i\times m_j}$, $g_i=1, 2,\cdots, l_i$, $k_j=1, 2,\cdots, m_j$. The value of matrix element $e_{ij}^{g_ik_j}$ is composed by structure b_{jk_j} and customer requirement f_{jl}, and $\boldsymbol{E}_{ij}=\boldsymbol{E}_{ji}$, $\boldsymbol{E}_{ii}=\boldsymbol{I}$.

(5) Relationships among requirements, functions and structures. The relationships among requirements, functions and structures are shown as Fig. 3.

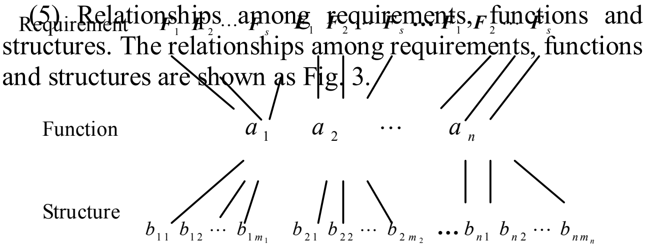

Fig. 3. Relationships among functions, structures and requirements

From Fig. 3 we can realize that there are the relationships between requirements and structures for each function, and the correlation matrix between functions and structures can be expressed according to customer requirements and structures which are correspond to the function. The components of block matrix $\boldsymbol{C}_i=(c_{i1},c_{i2},\cdots,c_{im_i})$ in Eq. (5) can be calculated out according to the relationships.

Suppose the weight of each requirement $\boldsymbol{F}_i$ is w_i ($i=1, 2, \cdots, s$), when input customers requirement vector $(f_{1g_1},f_{2g_2},\cdots,f_{sg_s})$, the elements of block matrix $\boldsymbol{C}_i$ equal to:

$$c_{jk_j}=\sum_{i=1}^{s} w_i e_{ij}^{g_i k_j}, \tag{8}$$

where j=1, 2,⋯, n, g_i=1, 2,⋯, l_i, k_j=1, 2,⋯, m_j.

So the elements of correlation matrix between functions and structures can be calculated out according to the elements of correlation matrix between requirements and structures.

(6) The interface of variable length gene. Total data from the above models need to be put into database in actual application. If a new requirement needs to be added, the fields of customer requirement table and correlation matrix between requirement and structure will be broken in the database, so variable gene design for requirement needs to be carried out. When the product structure in the database cannot match a new requirement, new product structure needs to be added, so variable gene design for structure can be carried out. The approach of adding and deleting can be given out by Eqs. (2) and (3). The inputting parameters included in new requirement section, the value of requirement section, the value of added requirement in correlation matrix between requirement and structure, new structure section and the value of structure section.

(7) Achieving a multi-object optimization model. The purpose of conceptual design is to choose the best group of structures, which makes the combination of functions and structures as well as the combination of structures and structures achieve optimization. So achieve a two-object's multi-object optimization model according to correlation matrix:

$$\begin{cases} \max\limits_{b_{1k_1}, b_{2k_2},\cdots, b_{nk_n}} \left(\sum\limits_{i=1}^{n} c_{ik_i}\right), \\ \max\limits_{b_{1k_1}, b_{2k_2},\cdots, b_{nk_n}} \left(\sum\limits_{i=1}^{n-1}\sum\limits_{j=i+1}^{n} d_{ij}^{k_i k_j}\right), \\ \text{s.t.}\quad c_{ik_i}\neq 0 \cup d_{ij}^{k_i k_j}\neq 0. \end{cases} \tag{9}$$

With different value of k_1, k_2,⋯, k_n, a design structure $b_{1k_1}, b_{2k_2},\cdots, b_{nk_n}$ can be obtained. In the restricted condition, for different function's structures the element $d_{ij}^{k_i k_j}\neq 0$ means if there are two structures which cannot combine together, that is $d_{ij}^{k_i k_j}=0$. The group of structures is not optimal.

5 Calculating Optimization Models by Genetic Algorithm

5.1 Segment genetic algorithm

We have elaborated segment genetic algorithm in Ref. [6]. Now simply state is as follows.

Definition 4: Mutual mutation operator. Suppose using binary code. For arbitrary an individual from the population, randomly choose a gene whose value equals to 1 and change it to 0. At the same time, randomly choose a gene whose value equals to 0 and change it to 1. Then we can get a new individual. This operator is called as mutual mutation operator. Corresponding operation is called as mutual mutation operation.

Segment genetic algorithm is compared with standard genetic algorithm, and there are some differences as follows.

(1) Coding method. Segment genetic algorithm makes use of binary multi-parameter cascade coding method, which means editing each parameter by binary coding, and links them together to build up an individual code which can express all parameters according to a given order.

(2) Segment crossover operation. Segment crossover operator is different from normal crossover operator. Individual coding is parted at parameter connecting points, and crossover operation is carried out by one or more connecting points random chosen as a crossover point according to a certain probability. There is no crossover point inside each segment.

(3) Segment mutual mutation operation. Segment mutual mutation operator is used instead of mutation operator in segment genetic algorithm. Firstly randomly choose mutual mutation segments. Secondly randomly choose mutual mutation points from these segments. Finally mutual mutation operation is carried out according to a certain probability.

5.2 Computation of multi-object optimization models

Calculate optimization model (1) by segment genetic algorithm and hybrid genetic algorithm, the steps is as follows:

(1)Individual coding and produce of original population. Individual coding is in use of binary multi-parameter cascade coding method as is stated above. Suppose the structure which can achieve function a_i is $\boldsymbol{B}_i=(b_{i1}, b_{i2},\cdots, b_{im_i})$, i=1, 2,⋯, n, individual coding can be expressed as:

$$(b'_{11}, b'_{12},\cdots, b'_{1m_1}, b'_{21}, b'_{22},\cdots, b'_{2m_2},\cdots, b'_{n1}, b'_{n2},\cdots, b'_{nm_n}),$$

where b'_{ij} equals to 0 or 1, and there is only one gene whose value is 1 in each segment. Original population is random produced according to this coding method.

(2) Design of genetic operator. Selection operation is applied by proportional selection operator combined with optimal preservation strategy. Firstly, calculate the selection probability of individual by proportional selection operator according to its fitness, then calculate the selection times of each individual according to selection probability and the random selection times should be less than the number M of population. Secondly, the optimal individuals are saved up and directly inherited to the next population without crossover and mutation operation by optimal preservation strategy. This is not only avoiding to strap into local minimum values, but also saving the optimal individual as

so far. Crossover operation adopts the segment crossover operator and one-point crossover operation. Mutual mutation operation uses segment mutual mutation operator as is stated above.

(3) Parallel selection operation. According to the number of sub-object functions in the multi-object optimization model, the whole population is averagely divided into some sub-population. Every sub-object functions can produce next generation in corresponding sub-population.

(4) Preserving Pareto optimal individuals. The Pareto optimal individuals in each sub-population do not participate in crossover operation and mutation operation and directly preserve in next generation sub-population.

(5) Sharing function operation. If the number of Pareto optimal individuals exceeds population scale, these Pareto optimal individuals need to be chose by means of niche sharing function approach so as to form new generation population.

Niche number can be expressed as

$$m_X = \sum_{Y \in P} s(d(X,Y)), \tag{10}$$

where $d(X, Y)$ is Hamming distance between X and Y.

Sharing function can be expressed as follows:

$$s(d) = \begin{cases} 1-\dfrac{d}{\sigma}, & \text{if} \quad 0 \le d \le \sigma, \\ 0, & \text{if} \quad d > \sigma, \end{cases} \tag{11}$$

where $\sigma>0$ expresses niche range.

(6) Confirmation of running parameters in genetic algorithm. The following several running parameters need to be confirmed: population size M, number of termination generation T, crossover probability P_c, mutation probability P_m, generation gap G.

6 Application Examples

The down-to-up conceptual design process is applied in the configuration design of a washing machine. The structure meeting the requirement can be selected automatically according to a number of key data for customer requirements. Even if the requirements are changed, that is the total number of requirement is increased or decreased, we can complete the design automatically by variable gene expression. The procedure is described as follows.

(1) Structure decomposition in washing machine design and bottom achievement structures. The function decomposition of washing machine includes external structure, engine type, and internal structure, etc. In order to simplify this problem, a washing machine is selected and divided into figure, impeller, and control, water supply and drainage. These four parts are taken as implementing structures of bottom function with different shapes. Each structure is shown in Table1 and vector $\boldsymbol{B}_1$, $\boldsymbol{B}_2$, $\boldsymbol{B}_3$, $\boldsymbol{B}_4$ act as their structure vectors.

(2) Achieving a correlation matrix between structures and structures. The matrix is achieved based on Eq. (6) as follows:

$$\boldsymbol{D} = \begin{array}{c} \\ \boldsymbol{B}_1 \\ \boldsymbol{B}_2 \\ \boldsymbol{B}_3 \\ \boldsymbol{B}_4 \end{array} \begin{array}{c} \begin{array}{cccc} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \boldsymbol{B}_3 & \boldsymbol{B}_4 \end{array} \\ \begin{pmatrix} \boldsymbol{D}_{11} & \boldsymbol{D}_{12} & \boldsymbol{D}_{13} & \boldsymbol{D}_{14} \\ \boldsymbol{D}_{21} & \boldsymbol{D}_{22} & \boldsymbol{D}_{23} & \boldsymbol{D}_{24} \\ \boldsymbol{D}_{31} & \boldsymbol{D}_{32} & \boldsymbol{D}_{33} & \boldsymbol{D}_{34} \\ \boldsymbol{D}_{41} & \boldsymbol{D}_{42} & \boldsymbol{D}_{43} & \boldsymbol{D}_{44} \end{pmatrix} \end{array},$$

where

$$\boldsymbol{D}_{12} = \begin{pmatrix} 1 & 3 \\ 3 & 5 \\ 5 & 3 \\ 5 & 1 \end{pmatrix}, \quad \boldsymbol{D}_{13} = \begin{pmatrix} 3 & 5 \\ 3 & 5 \\ 3 & 5 \\ 5 & 3 \end{pmatrix}, \quad \boldsymbol{D}_{14} = \begin{pmatrix} 3 & 5 \\ 3 & 5 \\ 5 & 3 \\ 5 & 1 \end{pmatrix},$$

$$\boldsymbol{D}_{23} = \begin{pmatrix} 5 & 5 \\ 5 & 5 \end{pmatrix}, \quad \boldsymbol{D}_{24} = \begin{pmatrix} 5 & 5 \\ 5 & 5 \end{pmatrix}, \quad \boldsymbol{D}_{34} = \begin{pmatrix} 5 & 5 \\ 5 & 5 \end{pmatrix}.$$

Table 1. Component of structures

Figure B_1	ImpellerB_2	Control B_3	Water supply and drainage B_4
Big b_{11}	Butterfly b_{21}	Mechanical b_{31}	General b_{41}
Middle b_{12}	Raised b_{22}	Electronic b_{32}	With pump b_{42}
Small b_{13}	–	–	–
Mini b_{14}	–	–	–

Only the elements of matrix $\boldsymbol{D}$ above the diagonal are used in optimization model, so the other elements of $\boldsymbol{D}$ can be ignored. This kind of matrix is complicated, but the data is fixed and does not change as the customer requirement. The correlation matrix is fixed as long as the every structure does not change.

(3) Achieving a correlation matrix between requirements and structures. The requirement indexes and their values are shown in Table 2. The values of the correlation matrix between requirements and structures are shown in Table 3.

Table 2. Index required by customers

Price $\boldsymbol{F}_1$	Power consumption $\boldsymbol{F}_2$	Libration $\boldsymbol{F}_3$	Figure $\boldsymbol{F}_4$	Water consumption $\boldsymbol{F}_5$
Inferior f_{11}	Economic f_{21}	Big f_{31}	Big f_{41}	More f_{51}
Intermediate f_{12}	Intermediate f_{22}	Little f_{32}	Small f_{42}	Few f_{52}
Top f_{13}	Waste f_{23}	–	–	–

(4) Variable length gene design. Suppose the washing machine required by the customer is medium price, intermediate power consumption, small libration, few water consumption and excellent clean index. Because the first four are listed in Table 2, but the last one is not included in the total requirement, the common algorithm is not suitable.

We need adopt the approach of variable length interface. The approach is to add the new item "excellent clean index" into the table, as Table 4 shown. Because there is no design structure of matching with excellent clean index in the former database, new structures like stick are added into Table 5.

Table 3. Correlation matrix between structure and requirement

Requirement		Structure									
		$\boldsymbol{B}_1$				$\boldsymbol{B}_2$		$\boldsymbol{B}_3$		$\boldsymbol{B}_4$	
		b_{11}	b_{12}	b_{13}	b_{14}	b_{21}	b_{22}	b_{31}	b_{32}	b_{41}	b_{42}
$\boldsymbol{F}_1$	f_{11}	0	1	5	5	5	0	5	1	5	1
	f_{12}	3	5	5	1	3	5	5	3	3	3
	f_{13}	5	5	1	0	1	5	1	5	3	5
$\boldsymbol{F}_2$	f_{21}	1	3	5	5	5	5	5	3	5	1
	f_{22}	3	5	3	3	5	5	3	3	3	3
	f_{23}	5	3	0	0	5	5	1	5	1	5
$\boldsymbol{F}_3$	f_{31}	5	3	3	3	1	3	3	3	1	3
	f_{32}	1	1	3	3	5	3	3	3	5	3
$\boldsymbol{F}_4$	f_{41}	5	5	1	0	3	5	3	5	5	5
	f_{42}	0	1	5	5	5	3	5	3	5	1
$\boldsymbol{F}_5$	f_{51}	5	3	1	1	5	5	5	5	5	5
	f_{52}	1	3	5	5	5	5	5	5	5	5

Table 4. New index required by customers

Price $\boldsymbol{F}_1$	Power consumption $\boldsymbol{F}_2$	Libration $\boldsymbol{F}_3$	Figure $\boldsymbol{F}_4$	Water consump-tion $\boldsymbol{F}_5$	Clean index $\boldsymbol{F}_6$
Inferior f_{11}	Economic f_{21}	Big f_{31}	Big f_{41}	More f_{51}	Excellent f_{61}
Intermediate f_{12}	Intermediate f_{22}	Little f_{32}	Small f_{42}	Few f_{52}	Good f_{62}
Top f_{13}	Waste f_{23}	–	–	–	Pass f_{63}

Table 5. Structure vectors

Figure $\boldsymbol{B}_1$	Impeller $\boldsymbol{B}_2$	Control $\boldsymbol{B}_3$	Water supply and drainage $\boldsymbol{B}_4$
Big b_{11}	Butterfly b_{21}	Mechanical b_{31}	General b_{41}
Middle b_{12}	Raised b_{22}	Electronic b_{32}	With pump b_{42}
Small b_{13}	Stick b_{23}	–	–
Mini b_{14}	–	–	–

The correlation matrix between customer requirement and product structure is changed correspondingly. According to variable length design idea, the content in Table 3 is not changed except lines 13, 14, 15 and row 7 are added into new elements. This change is shown in Table 6.

Structure-structure correction matrix should be changed due to the new structure added. According to variable length design idea, because only structure $\boldsymbol{B}_2$ is changed the $\boldsymbol{D}_{13}$, $\boldsymbol{D}_{14}$, $\boldsymbol{D}_{34}$ is not changed. The last one row is added in $\boldsymbol{D}_{12}$ and the last one line is added in $\boldsymbol{D}_{23}$ and $\boldsymbol{D}_{24}$. The changed matrix is shown as below:

$$\boldsymbol{D} = \begin{array}{c} \\ \boldsymbol{B}_1 \\ \boldsymbol{B}_2 \\ \boldsymbol{B}_3 \\ \boldsymbol{B}_4 \end{array} \begin{array}{c} \begin{array}{cccc} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \boldsymbol{B}_3 & \boldsymbol{B}_4 \end{array} \\ \begin{pmatrix} \boldsymbol{D}_{11} & \boldsymbol{D}_{12} & \boldsymbol{D}_{13} & \boldsymbol{D}_{14} \\ \boldsymbol{D}_{21} & \boldsymbol{D}_{22} & \boldsymbol{D}_{23} & \boldsymbol{D}_{24} \\ \boldsymbol{D}_{31} & \boldsymbol{D}_{32} & \boldsymbol{D}_{33} & \boldsymbol{D}_{34} \\ \boldsymbol{D}_{41} & \boldsymbol{D}_{42} & \boldsymbol{D}_{43} & \boldsymbol{D}_{44} \end{pmatrix} \end{array},$$

$$\boldsymbol{D}_{12} = \begin{pmatrix} 1 & 3 & 5 \\ 3 & 5 & 5 \\ 5 & 3 & 3 \\ 5 & 1 & 1 \end{pmatrix}, \quad \boldsymbol{D}_{13} = \begin{pmatrix} 3 & 5 \\ 3 & 5 \\ 3 & 5 \\ 5 & 3 \end{pmatrix}, \quad \boldsymbol{D}_{14} = \begin{pmatrix} 3 & 5 \\ 3 & 5 \\ 5 & 3 \\ 5 & 1 \end{pmatrix},$$

$$\boldsymbol{D}_{23} = \begin{pmatrix} 5 & 5 \\ 5 & 5 \\ 5 & 5 \end{pmatrix}, \quad \boldsymbol{D}_{24} = \begin{pmatrix} 5 & 5 \\ 5 & 5 \\ 5 & 5 \end{pmatrix}, \quad \boldsymbol{D}_{34} = \begin{pmatrix} 5 & 5 \\ 5 & 5 \end{pmatrix}.$$

Table 6. New correlation matrix between structure and requirement

Requirement	Structure										
	$\boldsymbol{B}_1$				$\boldsymbol{B}_2$			$\boldsymbol{B}_3$		$\boldsymbol{B}_4$	
	b_{11}	b_{12}	b_{13}	b_{14}	b_{21}	b_{22}	b_{23}	b_{31}	b_{32}	b_{41}	b_{42}
f_{11}	0	1	5	5	5	0	1	5	1	5	1
f_{12}	3	5	5	1	3	5	5	5	3	3	3
f_{13}	5	5	1	0	1	5	5	1	5	3	5
f_{21}	1	3	5	5	5	5	5	5	3	5	1
f_{22}	3	5	3	3	5	5	5	3	3	3	3
f_{23}	5	3	0	0	5	5	5	1	5	1	5
f_{31}	5	3	3	3	1	3	3	3	3	1	3
f_{32}	1	1	3	3	5	3	3	3	3	5	3
f_{41}	5	5	1	0	3	5	5	3	5	5	5
f_{42}	0	1	5	5	5	3	1	5	3	5	1
f_{51}	5	3	1	1	5	5	5	5	5	5	5
f_{52}	1	3	5	5	5	5	5	5	5	5	5
f_{61}	5	5	5	5	1	3	5	5	5	5	5
f_{62}	5	5	5	5	3	5	5	5	5	5	5
f_{63}	5	5	5	5	5	5	5	5	5	5	5

The input interface of variable length design is shown in Fig. 4, if click button 3, new values can be input in interface of Fig. 5.

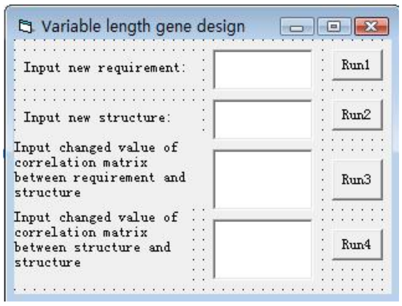

Fig. 4. Variable length gene design interface

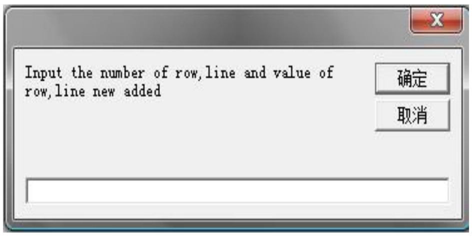

Fig. 5. Add new structure interface

(5) Achieving a correlation matrix between functions and structures. The value of the matrix between functions and structures can be got from the correlation matrix between requirements and structures. Each index value can be calculated from Eq. (3). The value of the matrix changes as customer's requirement changes.

Suppose the inputted requirement is (f_{12}, f_{22}, f_{32}, f_{52}, f_{61}), every weight value w_i (i=1, 2,···, 6; i≠4)=1/5, w_4=0. Put it into Eq. (5), the matrix is shown as below:

$$\begin{array}{c c} & \begin{array}{cccc} \boldsymbol{B}_1 & \boldsymbol{B}_2 & \boldsymbol{B}_3 & \boldsymbol{B}_4 \end{array} \\ \boldsymbol{C} = \begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} & \begin{pmatrix} \boldsymbol{C}_1 & & & \\ & \boldsymbol{C}_2 & & \\ & & \boldsymbol{C}_3 & \\ & & & \boldsymbol{C}_4 \end{pmatrix} \end{array},$$

where $\boldsymbol{C}_1$=(2.6, 3.8, 4.2, 3.4), $\boldsymbol{C}_2$=(3.8, 4.2, 4.6), $\boldsymbol{C}_3$=(4.2, 3.8), $\boldsymbol{C}_4$=(4.2, 3.8).

(6) Computation by segment genetic algorithm. Suppose parameter $\alpha=\beta=1/2$ and convert multi-object model of Eq. (9) into single-object optimization model:

$$\begin{cases} \max\limits_{b_{1k_1}, b_{2k_2}, \cdots, b_{nk_n}} \left(\alpha \sum\limits_{i=1}^{n} c_{ik_i} + \beta \sum\limits_{i=1}^{n-1} \sum\limits_{j=i+1}^{n} d_{ij}^{k_i k_j} \right), \\ \text{s.t.} \quad c_{ik_i} \neq 0 \cup d_{ij}^{k_i k_j} \neq 0, \end{cases} \tag{12}$$

Let n=4 and individual coding is in use of coding method mentioned above. There are 4 functions, so gene chain is divided into 4 sections. The length of each section is the same as the number of its structure. The length of the former gene section is 4, 2, 2, 2 and the total length is 10 as Table 1. The length of the latter gene section is 4, 3, 2, 2 and the total length is 11 as Table 5. All new structures are added in last position. For example: 00100010001 is a gene coding, we can only cross behind the fourth, seventh and eighth place and one-point crossover is used in this case. When take mutual mutation operation, randomly choose a gene section from the total four sections, then mutual mutation operation is inside this section. Operation parameters are M=20, T=100, P_c=0.9, P_m=0.6, G=0.8. The maximum value of fitness is 46 and the corresponding individual gene expression is (000000100010100). The selected structure is middle b_{12}, stick b_{23}, electronic b_{32}, with pump b_{42}, Which is fit for customer requirement. The operation result is shown in Fig. 6.

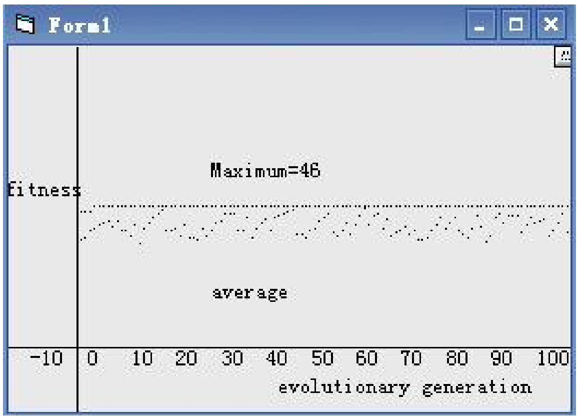

Fig. 6. Computation result of segment genetic algorithm

(7) Computation by segment genetic algorithm and hybrid genetic algorithm. By parallel selection genetic algorithm, the population is divided into two sub-populations and each object function in Eq. (9) is taken as fitness function of each sub-population. Let n=4 and carry out selection operation. Combine them to a whole population and carry out coding, crossover and mutual mutation operation by above-mentioned segment genetic algorithm. Keep Pareto optimization individual in each sub-population into next generation. Pareto optimal individuals with bigger Hamming distance are inherited to next generation by niche genetic algorithm. Computation result is six Pareto optimization results. These are shown in Table 7. Because there are two points of f_1 and f_2 repeated, four Pareto optimization results are shown in Fig. 7.

Table 7. All Pareto optimization results

Object f_1	Object f_2	Object f_1+f_2	Structure b_{1i}	Structure b_{2i}	Structure b_{3i}	Structure b_{4i}
14.8	30	44.8	1	3	2	2
15.6	30	45.6	2	2	2	2
16	30	46	2	3	2	2
16	30	46	3	1	2	1
16.8	28	44.8	3	3	2	1
15.6	30	45.6	4	1	1	1

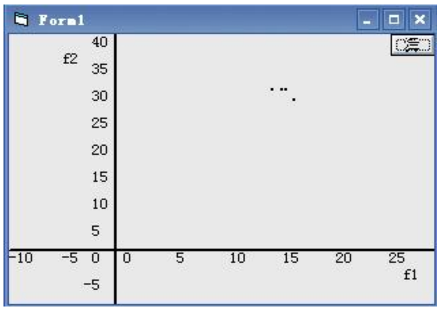

Fig. 7. Computation result of hybrid genetic algorithm

(8) Comparison and analysis of the result. At coding approach, segment genetic algorithms are different from standard genetic algorithms though the latter can also carry out the right result. The primary character of segment genetic algorithms is coding according to location and every location embodies the relationships among requirements. Segment genetic algorithms can implement

variable gene expression, so the problem of variable requirement is solved.

The two approaches for segment genetic algorithms and hybrid genetic algorithms are used in this paper. Either of all can arrive at satisfactory optimal solutions. The difference is that more Pareto optimization individuals can be found out if we use hybrid genetic algorithms for multi-object optimization models. Therefore the result of computation is more accurate.

In this case a nearly accurate result can be calculated if standard genetic algorithm is used, but the difference is present at coding approach. Section genetic algorithms completing variable gene expression according to coding depends on location and requirement relation can be achieved for each place, so the problem of variable requirement is solved, however, for standard genetic algorithms, variable requirement cannot be achieved according to coding by number arrangement. Therefore section genetic algorithm is better than standard genetic algorithms.

In this case section genetic algorithms combined with hybrid algorithms are used in calculation, satisfactory result can be obtained from either kind of algorithms. The difference is that more Pareto optimization units can be found if we use multi-object optimization hybrid algorithm, and more optimization results are obtained in this case.

7 Conclusions

In this paper a new approach for the bottom-to-top adaptive conceptual design is proposed by research on variable requirement and the variety of structure combination for complex products. The conclusions are summarized as follows:

(1) By means of variable length gene expression, new requirement, new structure and data of correlation matrix can be automatically added without change of the data in initial database. So as to new requirement of design is satisfied.

(2) By research on the relationships of correlation matrixes among requirements, functions and structures, a mathematic model for mutual transformation among three correlation matrixes is presented. A block diagonal matrix of correlation matrix between functions and structures is given in order to make the operation process more formulized.

(3) A multi-object optimization design model for selecting structure of product is achieved by the approaches of the constraint conditions of parameter, the correlation matrixes and making the sum of its element maximum

(4) An improved segment genetic algorithm is proposed for gene expression and variable length gene expression. Then the multi-object optimization model is calculated by segment genetic algorithm combined with parallel selection approach and niche sharing function. Finally a satisfied result is achieved.

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